Assessing Short-Run and Medium-Run Fishing Capacity at the Industry Level And
Its Reallocation

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Reducing harvesting capacity in fisheries is of international importance. In 1999, member nations of the United Nations Food and Agricultural Organization (FAO) agreed to an International Plan of Action to reduce fishing capacity. Two initial concerns were the acceptance of a workable definition of capacity and the development of methods to calculate capacity. FAO subsequently offered several definitions of capacity. A general definition of capacity is the output level over a given time period that a fishing fleet could expect to catch if the variable inputs are utilized under normal operating conditions given resource levels, technology, and other constraints. Concurrently, however, FAO and representatives of the member nations expressed concerns about reducing capacity at the national level (i.e., a reallocation of capital, labor, and other inputs) and with respect to both the short and long-run. In this paper, we present a possible approach for determining capacity at a more aggregate level than the vessel (e.g., fishery or region) with respect to the short and intermediate-run, and the allocation of fixed and variable inputs across different fisheries and regions. We extend one approach to measuring capacity of a firm to the case of an industry. Based on extensions of this specification, existing capacities are no longer fixed, but may be scaled up or down at will subject to a constant returns to scale technology. This allows for exploring plausible medium-term technological configurations at the industry level.

Keywords: Industry Capacity, Data Envelopment Analysis, Allocation

1.   INTRODUCTION

In February 1999, the Twenty-third Session of the Food and Agriculture Organization (FAO) Committee on Fisheries adopted an International Plan of Action (IPA) for the management of fishing capacity. A general definition of capacity offered in the IPA for capacity was the output level or catch over a given period of time that could be caught given fleet size and composition, resource conditions, market and economic factors, and the state of technology. The IPA definition was originally in terms of single vessels or operating units but was expanded to consider a fishing fleet or several fisheries. The IPA also recognized a need to consider economic factors when assessing capacity, but noted that appropriate data are seldom available.

In 1999, FAO sponsored a meeting on estimating and assessing capacity at a fishery, national, regional, and global level while also being able to assess capacity at the vessel level. A critical focus of this meeting was how to appropriately estimate an aggregate measure of capacity that recognized that capacity could flow between fisheries and geographical areas and that many fisheries involve multiple products and multiple inputs. Participants at the FAO meeting were unable to conclude how an aggregate measure of capacity that was also useful for resource management could be estimated.

In this paper, we present two potential approaches for assessing capacity at the industry level while also recognizing a need to have estimates of capacity at the vessel level. We also offer a potential framework for assessing capacity at the intermediate level with the goal of achieving an optimal industry structure through reallocations of inputs and outputs. Indeed, when groups of firms are not all achieving allocative efficiency, then it is well-known that the reallocation of resources could yield more production of at least one output while maintaining other output levels and utilizing the same

total input amounts. The lack of allocative efficiency at the individual firm level thus shows up as technical inefficiency of a group of firms (Diewert 1983). In this paper, this property is exploited by the models using the data envelopment analysis (DEA) framework of Färe et al. (1989, 1992) and later modified by Dervaux et al. (2000).

2.0 Capacity and Data Envelopment Analysis

Johansen (1968) offered a convenient definition that with slight modification can be shown to provide a definition of capacity that is relatively consistent with that defined in the IPA. If we let capacity be the maximum potential output that could be produced given that the availability of the fixed factors is not limiting, we have the Johansen definition. If we introduce resource constraints as states of technology and customary and usual operating procedures, we have the definition proposed in the IPA.

Defining capacity, however, is only one aspect of developing practical measures of capacity for fisheries. We must also have a relatively easy method for estimating capacity, particularly when data are quite limited as is often the case for fisheries. Färe et al. (1989) proposed a DEA framework as one approach for estimating the Johansen concept of capacity. In the Färe et al. framework, capacity equals the maximum potential or frontier level of output that could be produced given the fixed factors and full utilization of the variable factors. Alternatively, the Färe et al. framework can be thought of as the solution to a constrained optimization problem in which only the fixed factors bind production.

Data envelopment analysis (DEA) is a mathematical programming method that facilitates solutions to constrained optimization problems while providing information on the frontier or "best practice" technology. The DEA provides technical efficiency (TE) scores or measures of the distances that observations are from frontier levels. DEA can be used to assess TE relative to either an input or output orientation. TE from the input orientation indicates the maximum potential level by which all inputs may be radially reduced with no change in output level (e.g., a TE value of 0.75 indicates that all inputs may be reduced to 75% of their current level with no change in production). TE from an output orientation indicates the maximum potential level by which all outputs may be increased with no change in input levels. Scores of 1.0 from either an input or output orientation indicate TE. A third orientation is that of hyperbolic graph efficiency which permits outputs (and inputs) to be expanded (and reduced) by the same proportion; it may be generalized by what is called a directional distance function.

The method of DEA is described in Färe et al. (1985, 1994), Charnes et al. (1994), Coelli et al. (1998), and Cooper et al. (1999); we refer individuals interested in the details of DEA to the above referenced works. We provide a limited discussion of DEA specific to the assessment of capacity.

Returning to DEA and capacity, consider J producers that use N inputs to produce M outputs. We let u_{jm} equal the quantity of the mth output produced by the jth producer, and x_{jn} the level of the nth input used by the jth producer. Outputs and inputs are assumed to satisfy the following:

(i) $\quad u_{jm} \geq 0, \; x_{jn} \geq 0$

(ii) $\quad \sum_{j=1}^{J} u_{jm} > 0, \; m = 1,2,\ldots,M$

(iii) $\quad \sum_{n=1}^{N} x_{jn}, \; > 0, \; j = 1,2,..,J$

(iv) $\quad \sum_{j=1}^{J} x_{jn}, \; > 0, n = 1,2,\ldots,N$

(v) $\quad \sum_{m=1}^{M} u_{jm} > 0, \; j = 1,2.,\ldots,J$

Condition (i) imposes the assumption that each producer uses nonnegative amounts of each input to produce nonnegative amounts of each output. Conditions (ii) and (iii) require aggregate production of positive amounts of every output, and aggregate employment of positive amounts of each input. Conditions (iii) and (v) require each firm employ a positive amount of at least one input to produce a positive amount of at least one output. Zero levels are permitted for some inputs and outputs.

We next introduce the vector $z = (z_1,z_2,\ldots,z_J) \in R_+^J$ which denotes the intensity levels at which each of the J firms or producers are operating. The z vector allows us to decrease or increase observed production activities (input and output levels) in order to construct unobserved but feasible activities. More important, the z vector provides weights that are used to construct the linear segments of our piece-wise, linear technology (i.e., the technology constructed by DEA). The technology can be modeled from either an input or output orientation and relative to various returns to scale.

Since our assessment of capacity is based on an output orientation, we restrict our discussion to the output orientation. The output possibilities set can be used to construct a piece-wise technology. Under constant returns to scale (C) and strong disposability, (S) (strong disposability implies the producer has the ability to dispose of unwanted commodities with no private cost) we have the following:

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$$P(x \mid C,S) = \{u: u_m \leq \sum_{j=1}^{J} z_j u_{jm}, \, m = 1,...,M$$

$$\sum_{j=1}^{J} z_j x_{jn} \leq x_n, \, n = 1,...,N, z \in R_+^J\} \quad (1)$$

Non-increasing (NIRS) and variable returns to scale (VRS) can be modeled by imposing the following constraints: (1) NIRS--$\sum_j z_j \leq 1.0$, and (2) VRS--$\sum_j z_j = 1.0$.

With DEA, we can construct the piece-wise technology corresponding to the output set, $P(x \mid C,S)$

$$TE_{oj}(u_j, x_j \mid C,S) = \max_{\lambda,z} \theta \quad (2)$$

$$\text{subject to } \theta u_{jm} \leq \sum_{j=1}^{J} z_j u_{jm}, \, m = 1,...,M,$$

$$\sum_{j=1}^{J} z_j x_{jn} \leq x_{jn}, \, n = 1,...,N,$$

$$z_j \geq 0, \, j = 1\,2,...,J$$

where TE_{oj} is TE for an output orientation and indicates the maximum feasible or proportional expansion in all outputs; θ is the inverse of an output distance function and equals the ratio of the maximum potential output to the observed output level; and the z's are used to construct the reference technology. The value of θ is restricted to ≥ 1.0. If $\theta = 1.0$, production is technically efficient; if $\theta > 1.0$, production is inefficient and output levels could be increased by θ - 1.0.

3.0   DEA. Capacity, and Fisheries

The DEA offers a convenient framework for estimating capacity in fisheries because it permits maximum output to be estimated conditional only on the fixed factors. Alternatively, DEA easily facilitates the calculation of the concept of capacity proposed by Johansen (1968) and made operational by Färe et al. (1989).

Färe et al. (1989) illustrated that capacity at the plant level could be estimated by partitioning the fixed (F_x) and variable inputs (V_x) and solving the following output-oriented, DEA problem:

$$TE_{ocj} = \max_{\theta,z,\lambda} \theta \quad (3)$$

$$\text{subject to } \theta u_{jm} \leq \sum_{j=1}^{J} z_j u_{jm}, \, m = 1,...,M,$$

$$\sum_{j=1}^{J} z_j x_{jn} \leq x_{jn}, \, n \in F_x$$

$$\sum_{j=1}^{J} z_j x_{jn} = \lambda_{jn} x_{jn}, \, n \in V_x$$

$$z_j \geq 0, \, j = 1,2,...,J$$

$$\lambda_{jn} \geq 0,$$

where θ is a measure of TE ($\theta \geq 1.0$). If we multiply the observed output by θ, we obtain an estimate of capacity output. Capacity can also be estimated by solving problem (3) without the variable input constraints. This indicates the variable inputs are in fact decision variables, in line with the Johansen definition that assumes input fixity combined with unlimited access to the variable input dimensions.

Problem (3) imposes strong disposability in outputs and constant returns to scale. The constraints required for NIRS and VRS are, respectively, $\sum_j z_j \leq 1.0$ and $\sum_j z_j = 1.0$. Problem (3) was initially proposed by Färe et al. (1989) as an approach for assessing capacity when data were limited to input and output quantity information; that is, economic data such as cost and earnings information and information on input and output prices were not available. As such, problem (3) is a technological-engineering concept of capacity. Since estimates are based on actual data, however, estimates of capacity obtained from solutions to problem (3) implicitly reflect the underlying economics.

In addition to obtaining an estimate of capacity, problem (3) together with problem (2) may be used to estimate an unbiased measure of capacity utilization (CU). Färe et al (1989) demonstrated that the ratio of an output oriented measure of TE, with fixed and variable inputs included, to an output-oriented measure of TE, with variable inputs excluded, yielded a relatively unbiased measure of CU:

$$CU_j = \frac{TE_{oj}}{TE_{ocj}} \quad (4)$$

Although the focus of Färe et al. was on obtaining an unbiased estimate of CU, the Färe et al. CU measure permits an assessment of whether or not deviations from full capacity are because of inefficient production or less than full utilization of the variable and fixed inputs. In most calculations of CU, CU is determined in a non-frontier framework (e.g., peak-to-peak methods).

The solution to problem (3) also may be used to estimate a variable input utilization rate. The ith variable input utilization rate is estimated as follows (Färe et al. 1994):

$$\lambda_{jn}^{*} = \frac{\sum_{j=1}^{J} z_{j}^{*} x_{jvi}}{x_{jvi}}, \, n \in V_{x} \qquad (5)$$

where λ^{*} equals the ratio of the level of the ith variable input required to produce the capacity level to the observed usage of the ith variable input; the numerator equals the optimal level; and the denominator equals the observed usage of the ith variable input. A value of $\lambda > 1.0$ indicates a labor shortage relative to capacity production; $\lambda < 1.0$ implies excess labor.

The use of DEA to estimate capacity need not be restricted to the primal or technological-engineering concept of capacity. If sufficient data on input or output prices are available, it is possible to estimate TE, capacity, CU, and optimal variable input usage using a cost or revenue-based DEA problem. Färe et al. (2000) illustrate how TE, capacity, and CU for a multiproduct, multiple input technology can be estimated either directly by solving respective revenue maximization or cost minimization DEA problems similar to problem (3) or by exploiting the properties of duality.

4.0 Industry Capacity

FAO and numerous nations are seeking not only assessments of plant level (i.e., vessel) capacity, but also capacity at the fishery, industry, region, and national level. Alternatively, there is a desire to have measures of capacity at more aggregate levels than the plant. In addition, there is a preference to have the capability to assess reallocations of capital, labor, and other productive resources.

Assessing capacity at an industry or more aggregate level is considerably more complicated than determining plant-level capacity. First, there is the issue of whether or not there is a well-defined aggregate relationship between inputs and outputs that may be derived from the production relationships corresponding to individual producing units. Second, and specific to the assessment of aggregate capacity, there is the issue of whether or not there is an adequate level of variable inputs to produce the aggregate level of capacity. Third, what are the conditions for consistent aggregation.

The conditions for consistent aggregation have been the subject of numerous researchers (e.g., Nataf 1948; Malinvaud 1956; Green 1964; and Daal and Merkies 1984). Nataf, and later, Daal and Merkies, demonstrated that if all micro functions (e.g., production functions for individual decision-making units) were additively separable in their arguments, it would be possible to obtain a consistent aggregate.

Daal and Merkies (1984) commence with the following micro relationship:

$$u_{j} = f_{j}(x_{j1}, x_{j2}, \ldots, x_{jm}) \qquad (6)$$

where u is output, x_{ij} is the ith input for the jth producer, and we have $j = 1, \ldots, J$ producers. Consistent aggregation means that for each X within a given domain U,

$$u = G\{f_{1}(x_{11}, \ldots, x_{1m}), \ldots, f_{J}(x_{J1}, \ldots, x_{Jm})\} =$$
$$u = F\{g_{1}(x_{11}, \ldots, x_{j1}), \ldots, g_{m}(x_{1m}, \ldots, x_{Jm})\} = \qquad (7)$$
$$u = H(x_{11}, \ldots, x_{Jm})$$

The function G is an aggregator function that permits outputs of the individual producers to be aggregated. The function f_{I} is the production function of each producing unit; g_{I} is another aggregator function that permits aggregations of each input (e.g., $x_{m} = g_{m}(x_{1m}, \ldots, x_{Jm})$); F is a macro function that relates aggregate output, u, to aggregate inputs $(x_{1}, \ldots, x_{m})$; and H is referred to as the "atomistic macro function." In the above framework, consistent aggregation means that each vector $(x_{1}, \ldots, x_{m})$ resulting from the x_{jm} via the M functions, g_{m}, produce the same value of u via the function F as do the u_{j} by means of the function G (Pokropp 1972; Daal and Merkies 1984).

Daal and Merkies offer three examples, which permit consistent aggregation of firm level production to industry level production; we illustrate the simple linear relation:

linear relations in which the micro relations are

$$u_{j} = \alpha_{jo} + \sum_{m=1}^{M} a_{m} x_{jm} \text{ for } j = 1, \ldots, J; \qquad (8)$$

potential aggregation functions are

$$u = \sum_{j=1}^{JJ} y_{j} \text{ and } x_{m} = \sum_{m=1}^{M} x_{jm}; \text{ and} \qquad (9)$$

the macro relation is

$$u_{j} = a_{0} + \sum_{j=1}^{J} a_{m} x_{jm} \text{ with } a_{0} = \sum_{j} a_{jo}. \qquad (10)$$

Daal and Merkies derive similar aggregations based on the Cobb-Douglas and constant elasticity of substitution (CES) functions. Pokropp and Ijiri (1971) provide more generalized conditions for consistent aggregation.

Relative to assessing capacity for a fishery at a more aggregate level than the vessel, we adopt the statements of Klein (1946) and Daal and Merkies (1984): (1) Klein—inconsistencies are allowed if they lead to useful models; and (2) Daal and Merkies—realistic consistent aggregation is nearly impossible. We also note that if there are external effects (technological externalities), we cannot derive consistent aggregates; Chambers (1988) offers similar reasoning relative to obtaining an industry cost function aggregating over firm-level cost functions.

4.1 Capacity and the Short-run Johansen Model

For an industry technology with identical assumptions like the firm technology, the subvector radial input efficiency measure ($TE_i(X,Y)$) requires now solving a single LP (11) for the whole industry:

$$TE_I^{SR-Industry} = \underset{\lambda_I^{SR-Industry}, z}{Min} \quad \lambda_I^{SR-Industry} \qquad (11)$$

subject to $U_m \leq \sum_{j=1}^{J} z_j \hat{u}_{jm}, m = 1,...,M,$

$$\sum_{j=1}^{J} z_j \hat{x}_{jn} \leq \lambda_I^{SR-Industry} X_n, n \in F_x$$

$$-X_n + \sum_{j=1}^{J} z_j \hat{x}_{jn} = 0, n \in V_x$$

$$0 \leq z_j \leq 1, j = 1, 2,..., J$$

$$\lambda_I^{SR-Industry} \geq 0,$$

where: $U_m = \sum_{j=1}^{J} u_{jm}$ and $X_n = \sum_{j=1}^{J} x_{jn}$

where the hats above the parameters indicate that efficiency is being computed relative to the full capacity inputs and outputs of technology (i.e., the solutions from model (3). Each component of the activity vector is in the short run limited to be no larger than unity, so that current capacities cannot be exceeded. Another difference with the corresponding firm problem (3) is that the right hand sides of the constraints now contain aggregate outputs and fixed inputs available to the sector. The aggregate variable inputs have become decision variables, since there is no guarantee that their current allocation is sufficient to produce at full capacity (similar to the firm model (3)). The solution values of the activity vector indicate the combination of firms that could produce more or the same outputs with less or the same inputs in the aggregate. The efficiency score indicates the reduction in fixed sector inputs possible by a complete reallocation of production among individual firms given their current capacities.

An open issue is that the solutions for the optimal activity vector in (6) are not unique. This implies that if the model would be used to decide on which vessel to scrap, then proper decommissioning schemes should be put in place. Another problem with the above model formulation is that it may yield solutions where certain firms only work at "unrealistically" low levels of capacity utilization. For instance, if only 5% of a firm's capacity is needed in the optimal industry configuration, then it probably does not pay off to maintain the vessel in the fleet. However, one can easily include additional constraints putting a lower bound at the solutions for the activity vector $\overline{z}_j \leq z_j$, denoted by the bar.

It is obvious to further extend the above model in such a way as to incorporate additional policy constraints relevant for fisheries. For instance, a quota on a certain fish species (assume output k) can be simply added as an additional constraint: $U_k \leq \overline{U}_k$, where a bar denotes the quota amount. Aggregate industry output cannot exceed the quota. Current fishery policies similarly attach great importance on restricting total days at sea.

4.2 Capacity and a Medium term Johansen model

While the above model offers a coherent framework to explore the impact of short-run policies, it is equally possible to explore the optimal industry configuration in the medium term. This is done by releasing the restriction on the optimal activity vector (see Dervaux et al. (2000)). From an engineering point of view, it makes no sense to allow for an unrestricted scaling of vessels. Therefore, we propose to experiment with models including some upper bounds on the scaling of the activity vector reflecting prior information: $z_j \leq \overline{\overline{z}}_j$, denoted by the double bar.

4.3 Capacity: Single Output and Returns to Scale

Restricting attention to the case of a single output, we consider the case of j=1,…,J plants or activities that produce a single output, u_j, using a vector of fixed inputs $(x_{j1},…, x_{jF})$ and a vector of variable inputs $(x_{j1},…, x_{jV})$. The Johansen notion of capacity for a given plant (k') may be obtained from problem (3); we introduce, however, the following formulation to facilitate comparison with our proposed framework for assessing capacity at the industry level:

$$\varphi(x^j) = \underset{z_j X_n}{max} \sum_{j=1}^{J} z_j u_j \qquad (12)$$

subject to (s.t.)

$$\sum_{j=1}^{J} z_j x_{jn} \leq x_{jn}, n \in F_x,$$

$$\sum_{j=1}^{J} z_j x_{jn} \leq x_n, n \in V_x, \text{ and}$$

$$z_j \geq 0, j = 1,...,J.$$

where F_x indicates the fixed inputs and V_x indicates the variable inputs. The last n (V_x) constraints are nonbinding in the sense that the variable inputs may take any value; they are not restricted. Constant returns to scale (CRS) and free disposability of inputs and outputs are imposed on problem (12).

A major concern of resource managers is the possibility of improving technical efficiency by a reallocation of inputs among existing vessels or a

reconfiguration of an existing fleet (e.g., larger and more powerful vessels). Problem (12) does not consider a reallocation of fixed or variable inputs. It provides short-run estimates of capacity for an existing plant or producing unit. It does not provide information about intermediate to long-run possibilities or about industry capacity. In the next section, we focus on a measure of capacity for the industry, constant and other returns to scale, and potential options for assessing potential fleet reconfigurations.

4.4 Firm, Industry, and Returns to Scale

Given model (12) and our assumption of CRS, a measure of industry capacity that does not allow for reallocation of inputs among the different firms is the sum of the individual capacity outputs:

$$\phi(x^1,...,x^J) = \sum_{j=1}^{J} \varphi(x^j). \tag{13}$$

where x^j is a vector of all inputs corresponding to producer j.

On the other hand, if inputs can be reallocated among the J producers, we can have an alternative formulation of industry capacity:

$$\Gamma(X_1,...,X_N) = \max \sum_{j=1}^{J} z_j u_j \tag{14}$$

s.t.
$$\sum_{j=1}^{J} z_j x_{jn} \le X_n, n \in F_x,$$

$$\sum_{j=1}^{J} z_j x_{jn} \le X_n, n \in V_x,$$

$$z_j \ge 0, \ j = 1,...,J.$$

where $X_n = \sum_{j=1}^{J} x_{jn}, n = 1,...,N = F_x + V_x;$ the variable inputs may take any value. The relation between the two capacity measures (13) and (14) may be stated as

$$\Gamma(X_1,...,X_N) \ge \sum_{j=1}^{J} \varphi(x^j) = \phi(x^1,...,x^J). \tag{15}$$

To illustrate (15), assume there are only two producers (j=2), then

$$\varphi(x^1) = \max_{z_j x_n} \sum_{j=1}^{2} \gamma_j u_j; \ \varphi(x^2) = \max_{z_j x_n} \sum_{j=1}^{2} \sigma_j u_j \tag{16}$$

s.t.
$$\sum_{j=1}^{2} \gamma_j u_j \le x_{1n} \text{ and } \sum_{j=1}^{2} \sigma_j u_j \le x_{2n}, n = 1,...,N$$

$$= F_x + V_x \text{ and } \gamma_j \text{ and } \sigma_j \ge 0, j = 1,2.$$

We next denote the optimal intensity variables as λ_j^* and σ_j^* and add the two optimization problems together; we then have

$$\max \sum_{j=1}^{2} (\gamma_j^* + \sigma_j^*) u_j \tag{17}$$

s.t.

$$\sum_{j=1}^{2} (\gamma_j^* + \sigma_j^*) x_{jn} \le X_n = \sum_{j=1}^{2} x_{jn}, n = 1,...,N, \text{ and}$$

γ_j and $\sigma_j \ge 0, j = 1,2$. If we now consider $\gamma_j^* + \sigma_j^* = z_j$ and CRS, $z_j \ge 0.0$, the additive problem (17) is a sub-problem of (14), which proves the inequality in (15). Given the possibility of allocation, problems (14) and (17), it is inappropriate to replace the inequality in (15) with an equality constraint.

Problems (12) through (17) were all subject to constant returns to scale. Variable (VRS) or non-increasing returns to scale (NIRS), however, also may be desirable technical conditions to consider relative to the technology.

Problems (12), (16), and (17) can easily be modified for VRS and NIRS by imposing the appropriate constraints on the intensity variables. If the sum of the intensity variables is constrained to 1.0, we have VRS; if the sum is constrained to $\le$ 1.0, we have NIRS. It is a different matter, however, to impose VRS and NIRS on the industry specification (problem (14)). If we attempt to impose the constraint that the sum of the intensity variables equals 1.0 (i.e., VRS), we will seriously underestimate the potential capacity output. If we impose the restriction that each intensity variable corresponding to each firm in the industry model is between 0 and 1.0, we will implicitly restrict any potential reallocation of inputs. In both cases, our total capacity output will be less than or equal to observed aggregate output.

If we permit a reallocation of inputs and modify the constraints such that the sum of the intensity variables equals the number of observations (J), we obtain the VRS technology; the NIRS technology for the industry may be estimated by imposing the restriction that the sum of the intensity variables is less than or equal to J). Unfortunately, we may obtain some very unrealistic results by permitting unrestricted allocations of the fixed and variable factors (e.g., extremely large vessels).

4.5 Alternative Firm and Industry Specifications

In this section, we present the approaches of Färe et al. (1992) and Dervaux et al. (2000) for assessing capacity at the industry level. Both approaches impose CRS, but they may be modified for VRS and NIRS; the theoretical

aspects of these two approaches with VRS and NIRS, however, have not been fully examined. The Färe et al. (1992) is limited to a single output technology. Although the Dervaux et al. (2000) approach accommodates multiple outputs, it may underestimate capacity output when none of the fixed and variables factors may be reallocated; alternatively, the estimate of industry capacity may not equal the sum of estimated firm-level capacities.

Färe et al. (1992) demonstrated that under CRS, the sum of individual capacity levels equals the potential capacity output of the industry. The Färe et al. model is a hybrid model that permits allocation of those factors that can be reallocated while restricting the allocation of those factors that may not be allocated. It is an industry-based model that permits TE and capacity to be calculated relative to each firm and to the industry.

The Färe et al. model is as follows:

$$F(x_L^1,...,x_L^J, X_{L+1},...,X_{L+1}) =$$

$$\max_{\lambda_j^i} \left(\sum_{j=1}^{J} \lambda_j^1 u_j + \sum_{j=1}^{J} \lambda_j^2 u_j + ... + \sum_{j=1}^{J} \lambda_j^J u_j \right) \qquad (18)$$

$$\textit{s.t.} \ (\text{Firm } 1) \ \sum_{j=1}^{J} \lambda_j^1 x_{jn} \leq x_{1n}, n = 1,...,L,$$

$$(\text{Firm } J) \ \sum_{j=1}^{J} \lambda_j^J x_{jn} \leq x_{1n}, n = 1,...,L,$$

$$\text{Allocatable inputs} \left(\sum_{j=1}^{J} \lambda_j^1 u_j + \sum_{j=1}^{J} \lambda_j^2 u_j + ... + \sum_{j=1}^{J} \lambda_j^J u_j \right)$$

$$\leq X_n = \sum_{j=1}^{J} x_{jn}, n = L+1,...,N,$$

$$\lambda_j^i \geq 0, j = 1,...,J.$$

Inputs 1 through L are non allocable or firm-specific inputs while inputs L+1 through N may be allocated across firms. The restriction that $\lambda \geq 0$ imposes CRS on the technology.

With the hybrid model of Färe et al. (1992, it is possible to construct both firm and industry efficiency measures. A measure of industry TE is

$$\left(F(x_L^1,...,x_L^J, X_{L+1},...,X_{L+1}) / \sum_{j=1}^{J} u_j \right) \qquad (19). \quad \text{Firm j's}$$

optimal contribution to maximum potential industry

output is $\sum_{j=1}^{J} \lambda_j^{i*} u_J$, where λ^* denotes the optimal

intensity. Firm j's efficiency as part of the industry is

then $\left(\sum_{j=1}^{J} \lambda_j^{i*} u_J / u_j \right)$. We may conclude that when all

inputs may be reallocated, industry output is at least as large as when only some inputs may be allocated, and

when no input may be reallocated, industry output is smallest.

Dervaux et al. (2000) propose a different approach. In addition to the input-oriented model in (11), they proposed an output oriented model for the industry that also permits an assessment of allocating fixed and variable inputs while accommodating multiple outputs:

$$\left(DF_o(x_j, u_j) \right)^{-1} = \max_{\lambda, z_j, X_n^{vo}} \lambda \qquad (20)$$

s.t.

$$\sum_{j=1}^{J} u_{jm} z_j + U_m z_{j+1} - s_m = \lambda U_m, m = 1,...,M,$$

$$\sum_{j=1}^{J} x_{jn}^f z_j + X_n^f z_{j+1} + e_n = X_n^f, n = 1,...,N',$$

$$-X_n^v + \sum_{j=1}^{J} x_{jn}^v z_j + X_n^v z_{j+1} = 0, n' = 1,...,N,$$

$$z_j \geq 0, z_{j+1} \geq 0, X_n^v \geq 0, \lambda \geq 0, j = 1,...,J.$$

where DF_o is an output distance function, x_{jn}^f is a fixed input for the jth firm, x_{jn}^v is a variable input for the jth firm, and X_n^F and X_n^v are the nth fixed and variable inputs for the industry.

5.0 An Empirical Illustration

In this section, we illustrate the approaches of Färe et al. (1992) (model 18) and Dervaux et al. (2000) (model 20). We modify the Dervaux et al. model, however, by eliminating the j+1 intensity variable. We restrict our example to a single-species fishery—the U.S. northwest Atlantic sea scallop, *Placopecten magellanicus*, fishery. We have panel data on annual activity for nine vessels operating between 1987 and 1990. Data include output levels (landings of scallop meats per vessel per year), days at sea, man-days, stock abundance, and vessel characteristics (gross registered tonnage—GRT, engine horsepower—HP, and dredge size in feet). We use annual averages in an attempt to reflect customary and usual operating procedures. We consider the vessel characteristics as the fixed factors and days and man-days as the variable factors. Stock abundance, measured in terms of average baskets per tow per year, is considered as a state of technology and as both an allocable and non-allocable factor.

Vessel size ranged from 124 to 190 GRT Table 1). Engine horsepower varied between 520 and 620. Vessels used only two dredge sizes—13 and 15 feet. The annual average landings per vessel per year varied from a low of 127,733 pounds to a high of 172,229 pounds of sea scallop meats. The average days per sea per year ranged from 226.5 to 258.8 (Table 2). Man-days ranged between 2231 and 1475. Stock abundance varied from 1.95 to 3.3.

Table 1. Vessel characteristics: 9 sea scallop vessels

Vessel	GRT	HP	Dredge
1	181	620	15
2	125	520	13
3	190	520	15
4	124	620	13
5	130	520	15
6	135	520	15
7	129	520	15
8	137	520	15
9	131	520	13

Table 2. Average days, man-days, catch, and abundance[a]

Vessel	Catch	Days	Man-days	Abundance
1	172,229.0	255.3	2,474.7	3.3
2	127,733.3	248.5	2,410.4	2.5
3	140,726.5	226.5	2,260.2	3.1
4	135,843.3	255.8	2,443.9	2.6
5	143,256.5	239.3	2,231.4	2.9
6	169,924.8	258.8	2,336.0	3.2
7	142,264.0	244.0	2,294.1	2.8
8	137,132.5	242.5	2,357.8	2.8
9	129,667.5	235.0	2,227.0	2.6

[a]Days at sea is a measure of the number of days a vessel was at sea; Man-days equals the product of crew size and days at sea per year; stock abundance is a measure of number of baskets per tow per trip weighted by days per trip to obtain an annual measure.

Initially, we solve model (18) using only fixed inputs and imposing the condition that no inputs may be reallocated (Table 3). This provides estimates of TE and capacity for each vessel and the industry. Estimated capacity for the industry is 1,367,013 pounds of scallop meats; TE for the industry is 1.05. Solving model (18) again but including the variable inputs (days at sea and man-days) and allowing the variable factors to be allocable yields the same solution since the fixed factors limited output. If we then allow both the fixed and variable factors to be allocable, we obtain the solution that only one very large vessel should be in the fleet (1,088 GRT with 4,192 HP).; with model (18), however, the problem of obtaining unrealistic or impractical solutions can easily be resolved by imposing additional constraints on vessel characteristics (e.g., vessel size must be ≤ 300 GRT). TE for the freely allocable cases equals 1.055. Last, model (18) can easily accommodate restrictions on either total allowable catch for the industry (i.e., an industry wide quota) and on total allowable days at sea.

Table 3. Technical efficiency and capacity output

Boat	Technical Efficiency[a]	Intensity Variable[a]	Capacity Output[a]	Output[b]
1	1.00	1.00	172,229	0
2	1.04	0.78	132,754	1,370,019
3	1.17	0.97	164,615	0
4	1.02	0.81	138,064	0
5	1.07	0.91	153,994	0
6	1.00	1.00	169,925	0
7	1.05	0.88	148,684	0
8	1.08	0.88	148,684	0
9	1.06	0.81	138,064	0

[a]Indicates the values corresponding to the case when none of the fixed factors may be reallocated.
[b]Allows allocation of all fixed and variable factors.

We next solve model (20) (i.e., the Dervaux et al. model). If no fixed inputs may be reallocated, we obtain vessel and industry TE scores of 1.0 and the values of all intensity variables equal 1.0. Färe et al. (1992) demonstrated that model (20) and similar models in which the factors could not be reallocated would limit the maximal industry output to being no more than observed aggregate output. If we include all variable inputs and permit free allocation, we obtain the same industry output as obtained from model (18)—1,370,019 pounds of meats; the corresponding TE for the industry is 1.055. We also obtain the same unrealistic solution that there should be one very large vessel (1,088 GRT with 4,192 HP). We can, however, impose additional constraints on the vessel characteristics to depict more realistic vessel configurations.

We next solve models (18) and (20) with constraints imposed on the vessel characteristics and the potential stock abundance (Table 4). We include both variable and fixed inputs. We permit vessels to be as large as 300 GRT; have 1200 HP engines; and operate 17 foot dredges. These are reasonable size limitations given vessel characteristics of the present fleet and known operating characteristics. We also allow stock abundance to be reallocated up to a limit of 6.0; this is because larger vessels using 17 foot dredges typically yield about double the level caught by 15 foot dredges.

Table 4. Value of intensity variables

Vessel	z-values	
	Firm-Model[a]	Industry Model[b]
1	1.13	1.13
2	1.13	0.50
3	0.00	0.50
4	1.13	1.00
5	1.13	1.13
6	1.13	1.13
7	1.13	1.13
8	1.13	1.13
9	1.26	1.31

[a]All estimated values are with respect to vessel 6.
[b]Estimated values are with respect to each vessel.

The two models do not yield equivalent solutions Model (18), the Färe et al. model, predicts a potential capacity output of 1,370,019 pounds by eliminating vessel 3 and scaling all other vessels, except vessel 9, by 1.13; vessel 9 should be scaled by 1.26. All rescaling is with respect to vessel 6. Model (20) yields a TE of 1.005; this is again a reflection of limiting the potential allocation of fixed and variable inputs. Total potential output estimated by model (20) is 1,306,400 pounds of scallop meats. The original model (20) proposed by Dervaux et al. estimates TE and capacity output to equal, respectively, 1.018 and 1,321,619 pounds of meats.

6.0 Summary and Conclusions

Although our original intent was to provide several models and options for examining industry capacity while permitting reallocation of inputs, imposing quotas on outputs or inputs, and obtaining TE values for firms and the industry, it appears that our efforts were limited relative to our objectives. We were not able to adequately resolve problems associated with imposing VRS and NIRS. We obtained identical solutions for VRS and NIRS for the firm and industry models, but only if we allowed all inputs to be allocable and imposed the restriction that the sum of the intensity variables had to be ≤ 1 (NIRS) or equal to 1 (VRS) for the hybrid model of Färe et al. and J (the number of observations) for the industry model. The Färe et al. (1992) model easily facilitates calculation of firm and TE values, capacities, and the allocation of fixed and variable inputs, but it is primarily a single product model. Work is presently being conducted to allow the Färe et al. model to handle multiple output technologies. In addition, research on the use of the more conventional DEA formulations, but permitting resource allocations, is presently being conducted by the authors. VRS and NIRS may also be imposed by the Färe et al. (1992) model, but the appropriateness of imposing these technologies on the industry remains uncertain. The Dervaux et al. (2000) model does permit firm and industry TE values to be calculated for multiple output technologies, but may be limited in that it underestimates capacity output unless all factors can be allocated.

Considerably more research needs to be conducted on estimating capacity at the fishery or aggregations larger than the vessel. Desired by resource managers and fishery administrators are (1) estimates of capacity for multiple-species fisheries; (2) determination of optimum allocations of resources; (3) the ability to determine an optimum reconfiguration of fleet given limits on total allowable catches and days at sea; and (4) the ability to target vessels for removal from the fleet in the event of formal capacity reduction programs. The models presented in this paper offer an initial framework for assessing the capacity of a fishery.

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